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NONLINEAR COST ESTIMATES AT COMPLETION ADJUSTED WITH RISK CONTINGENCY

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ABSTRACT

Forecasting the final cost with Earned Value Management (EVM) and managing contingency budgets during the project execution have been traditionally considered as two separate streams of project management research. In an attempt to combine the two areas for the purpose of reflecting the risk impact on the cost forecast, this paper presents a cost estimate at completion (CEAC) methodology adjusted with risk contingency. The proposed method is a refined Earned Schedule (ES) based nonlinear CEAC model modified with a new parameter representing the S-shaped contingency consumption as a portion of the project budget at completion. The model is validated on eight construction projects and its estimates' accuracy and stability with a varying contingency parameter value in the early, middle, and late stages are evaluated.

The cost–schedule-risk relationship represented in the model is a contribution to creating a stronger connection between EVM and contingency cost management theories through capturing the interconnected dynamics between a cost baseline and contingency accounts of ongoing projects. As a practical implication, the model is a tool for integrating the contingency consumption into nonlinear CEAC models for accurate and stable cost forecasting especially during the early and middle stages of project execution.

1. Introduction

Estimating the final cost at completion of ongoing projects is a critical and essential part of project monitoring and control. Despite application of rigorous project management methodologies, various risk factors may affect the successful completion of a project *(Baloi and Price, 2003)*, so that reliable metrics for cost estimates are needed as a support for project managers to make decisions on how to correct the project's actual performance. Project managers rely on performance indicators to identify potential problems and to implement corrective actions that can help bringing programs back in line with predetermined objectives. For this purpose, Earned Value Management *(EVM)* has been used as a useful methodology for tracking projects and providing time and cost estimates at completion *(Lipke et al., 2009)*. EVM allows to compute schedule and cost performance indices *(SPI and CPI, respectively)*, which are further used to predict final time and cost estimates at completion.

However, studies addressing the reliability of time and cost forecasts based on the above two indices are subject to some limitations *(Christensen, 1993; Authors, 2013)*. Firstly, traditional index-based EVM forecasts are based on past project performance, which may not always reflect the project future behavior and potential uncertainties that impact on cost performance *(Christensen et al., 1995)*. Secondly, due to difficulties in accurate gauging the project progress, the method may have estimate errors resulting in the predictions be unreliable, especially in the early stages of the project execution *(Kim and Reinschmidt, 2011)*. Thirdly, EVM-based estimates do not consider the process of managing risk as an intrinsic factor of project performance and fail to integrate the dynamics of consumption of the cost contingency during the project execution *(Ford, 2002; Author et al., 2016)*.

Even though various techniques have been developed over the years to overcome the above limitations, there is still the need for methodologies able to integrate cost estimates at completion with cost contingency management. In fact, the processes of estimating cost at completion and managing risk contingencies are often used separately to study the project future performance and are rarely integrated *(Xie et al., 2012)*.

These considerations triggered the interest in developing a cost estimate at completion *(CEAC)* methodology that integrates cost contingency management. In particular, building on the works carried out by the Authors *(2013; 2014)*, we present a methodology for improved CEAC of an ongoing project that considers the consumption of the cost contingency budget as a factor of final project total cost.

The paper is organized as follows. First, we explore the pertinent literature and provide the background for the research. Then, the CEAC method integrated with cost contingency to capture project risk profile is presented. Third, to gain an understanding of the model applicability, a full application of the proposed methodology to a case project is given together with the model's accuracy, stability and sensitivity analyses. Then, we discuss the results obtained by the application of the proposed forecasting method to eight construction projects. Finally, we summarize the main conclusions and highlight future research directions.

2. Pertinent Literature

Based on index-based EVM, linear CEACs may be obtained using several forecasting methods each grounded on different assumptions about the future performance of the project *(PMI, 2013)*. Common formulations are based on the hypothesis that past performance is significantly representative of future behavior so that remaining budget to complete the project is linearly adjusted by past performance indices *(Anbari, 2003)*. Under such index-based linear assumptions, CEAC is defined as the ratio of the original cost baseline estimate of the project, here named as the budget at completion *(BAC)*, to the cost performance index *(CPI)*, or to a combination of CPI and SPI. The assumption of combining CPI and SPI implies that the final cost is additionally influenced by schedule performance. In particular, CPI is defined as the ratio of Earned Value *(EV)* to Actual Value *(AV)* and SPI as EV to Planned Value *(PV)*, both expressed in monetary units. However, the usage of SPI computed in, e.g., dollar amounts, fails to predict late-stage estimates as its value tends to one as the project tends to completion, i.e.: EV tends to converge to PV. Therefore, Lipke *(2003)* introduced a seminal refinement to this limitation proposing the use of Earned Schedule *(ES)* to calculate SPI and express the index in time units. ES is a measure of schedule performance expressed in time units as the ratio of ES to the actual time of the project and is used to compute SPI*(t)* defined as ES over the actual time of measurement. Comparative studies showed that the ES-based linear CEAC are more accurate and reliable than the estimates based on EV expressed in cometary units *(Kim et al., 2003; Cioffi, 2005; Lipke et al., 2009)*.

However, these methods can result unreliable especially in early-stage estimates because of few available EVM data. In addition, such estimates are considered as just dependent on past performance, which may fail to consider variations that arise due to future risk and uncertainty *(Fleming and Koppelman, 2006; Kim and Reinschmidt, 2011)*.

To overcome these limitations, some methodologies have been being developed that can bring improvements to EVM-based CEACs *(Zwikael et al., 2000; Willems and Vanhoucke, 2015)*. On the one hand, select works have been trying to use linear or non-linear regression models in order to provide more reliable CEAC formulae. Such regression models provided refined fitting to the S-curves of cumulative cost since the early stages of a project *(Cioffi, 2005; Lipke et al., 2009)*. As part of this stream of research, cost forecasts proved more reliable when integrating EVM into regression-based S-curve fitting *(Authors, 2013)*.

On the other hand, some authors have been integrating other methods and simulations into EVM to better capture the influence of uncertainty and risk as a determinant of future project performance. With this regard, Vanhoucke *(2011)* used Monte Carlo simulations to measure and evaluate the efficiency and quality of corrective actions of proposed bottom-up and top-down project tracking approaches to bring a project back on track. Pajares-López and Paredes *(2011)* integrated variability and risk analysis methodology into EVM-based approaches. Acebes et al. *(2015)* proposed the approach with Monte Carlo simulations to obtain information about the expected behavior of the project to reveal probabilities of success in expected cost and time estimates. Kim and Kim *(2015)* presented a project duration forecast framework with the purpose of detecting false early warnings and misleading trends that consist of forecast sensitivity evaluation, forecast risk compatibility check, and independent sanity checks using probabilistic models. Du et al. *(2016)* applied Markov chain simulation to probability distribution of the cost performance indicators for each period of a project to predict CEAC using the summation of each simulated period cost. However, based on this literature review, we revealed that most of the studies with simulations focus primarily on schedule performance and time estimates rather than on cost forecasting.

As part of this second stream of research, some works appropriately consider cost contingency management as an integral and important part of project monitoring. In fact, cost contingencies have the objective of covering probable cost increases above target estimates. Risk contingencies should be not only properly calculated and assigned in the budget estimation process, but also wisely consumed and controlled during the project execution *(Barraza and Bueno, 2007)*. With this regard, Cioffi and Khamooshi *(2009)*, considering project risks with corresponding impacts and probabilities, developed a method to estimate the total potential impact at a given certainty to allow project managers set aside corresponding contingency funds. Xie et al. *(2012)* presented a method for project cost contingency forecasting and updating it based on value at risk at a certain confidence level during the project execution.

Actually, the managerial process of defining, monitoring and controlling the cost contingency during the project execution may influence the CEAC methodology and calculation *(Ford, 2002)*. However, limited literature explores how the risk contingency is managed during the project development in order to investigate the impact of such practice on project performance and CEAC formulae *(Author et al., 2016)*. This paper is aimed at filling this research gap by exploring the integration between CEAC methodologies and cost contingency management. In particular, it proposes a mixed index-regression model adjusted with estimated cost contingency. Such a model promises to provide for accurate and reliable CEACs.

3. Contingency-Adjusted CEAC Formula

The new proposed CEAC methodology takes into account the influences of both the progress performance and contingency cost utilization during the execution of a project. It is based on the model proposed by Authors *(2014)*, referred hereafter to as the base model. With the purpose of improving and extending CEAC methodologies, the base model uses a Gompertz growth model *(GGM)* and incorporates the ES-based estimate of the duration of the project. A generic model of GGM is given in Equation 1 *(Authors, 2014)*.

The application of the base model requires the determination of the α, β and γ parameters of the GGM estimated using non-linear regression analyses. The α is the future value asymptote of the model that represents the final cost *(which is never attained)* as time x tends to infinity *(Seber and Wild, 1989)*, the β parameter is the y-intercept indicating an initial budget size, and the γ is a scale parameter that governs the cost growth rate. Then, CEAC can be calculated using these parameters with the added integration of ES, which has the aim of reflecting the progress of work performed into the cost estimate. The resulting CEAC for each given time x is given in Equation 2.

$$GGM(x)=e[e(x]$$

EQUATION 1

$$CEAC(x) = AV(x) + (GGM(CF(x)) - GGM(x)) * BAC$$

EQUATION 2

where AV(x) is the actual cost of work performed incurred at time x, BAC the budget at completion, here referred to as the originally estimated cost baseline, and CF(x) is the completion factor, which is defined as the inverse of SPI(t) computed using the ES method. Therefore, the CF(x) equals one when the project is on time, less than one when it is ahead of schedule and greater than one if it is experiencing a delay. The decision to use this forecasting model as the basis for the development of a new algorithm comes from its good level of accuracy and computational simplicity *(Authors, 2014; Hazir, 2015)*.

The new methodology proposed in this paper integrates the risk contingency cost component into the given base model. A contingency budget, which include all management contingency reserves for unplanned changes to project scope and cost *(PMI, 2013)*, is usually assessed using various available quantitative methodologies *(Touran, 2003; Mak and Picken, 2000)* and added at the beginning of the project to the cost baseline estimate in order to come up with a risk-adjusted budget at completion, here named to as BAC_{adj}. As long as the activities required to execute a project unfold, the cost baseline is cumulatively spent according to an S-shaped curve line that is well fitted by the GGM identified by the base model. Similarly, the contingency budget is a reserve account that is likely to be consumed along the project execution as per a reversed S-curve line, which can be modelled via a GGM (**Figure 1**). As far as the project progresses, the total initial contingency budget is going to be gradually used by the project team for activating risk corrective actions until most of the contingency cost account is spent *(Gutierrez and Kouvelis, 1991)*. Indeed, it can be reasonably assumed that the available remaining contingency cost is gradually spent with the same, although reverse, behavior of PV progress. Under the simplified assumption that the initial contingency budget is a predetermined k percentage portion of the BAC, the curves of cumulative BAC and cumulative contingency budget can be modelled as per **Figure 1**.

Under these assumptions, the risk contingency cost at any time x can be written as per Equation 3.

$$GGM(X)_{Risk} = \alpha - GGM(x)*k$$

EQUATION 3

In this way, GGM(x) estimated by non-linear regression is used to describe both the accumulation of actual cost incurred and the consumption of the contingency budget: at any point in time x, with corresponding CF(x), the project sums actual cost and residual contingency. Moreover, the introduction of the CF(x) allows to capture the trend of risk contingency by using it as a point on Equation 3. Therefore, the BAC is corrected with the residual contingency cost, which changes at every time x with behavior represented in **Figure 1**. The resulting BAC adjusted (BAC_{adj}) is modeled by Equation 4.

$$BAC_{adj} = BAC * \{1 + k[\alpha - GGM[CF(x)]]\}$$

EQUATION 4

k is the contingency cost expressed as a percentage of BAC.

By replacing the initial BAC with BAC_{adj} into Equation 2, one can obtain Equation 5.

$$CEAC(x) = AC(x) + \{GGM[CF(x)] - GGM(x)\} * BAC_{adj} = AC(x) + \{GGM[CF(x)] - GGM(x)\} * BAC * \{1 + k[\alpha - GGM[CF(x)]]\}$$

EQUATION 5

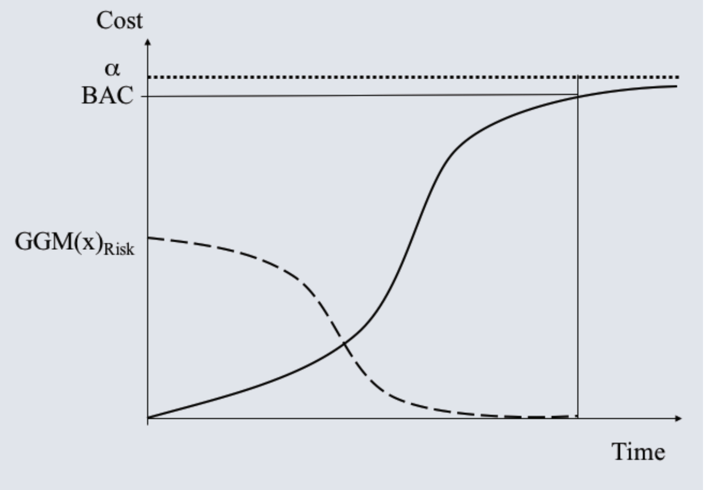

FIGURE 1. *Behavior of cumulative BAC and contingency budget*

4. Methodology

The proposed risk-adjusted CEAC model is tested on eight cases of various infrastructure, building construction and renovation projects with EVM data retrieved from the literature. The projects are listed in **Table 1**, where the columns report the number, literature source, Planned Duration *(PD)*, Actual Time *(AT)*, status at final completion, BAC and actual cost at completion *(CAC)*, respectively. The projects are purposefully of varied nature and range of PD and BAC to better explore the applicability of the proposed methodology. They also present various combinations of final cost and time performance compared to their original targets: four projects end with cost overruns and delayed finish *(CO-LF)*, two with cost underrun and late finish *(CU-EF)*, one

Project	Source	PD	AT	Status	BAC	CAC
1	Shokri-Ghasabeh and Akrami (2009)	15	16	CO-LF	57,747,300,000	61,564,285,700
2	Khamidi et al. (2011)	10	12	CO-LF	58,000,000	59,183,600
3	Vandevoorde and Vanhoucke (2006)	9	13	CU-LF	360,738	349,379
4	Vandevoorde and Vanhoucke (2006)	9	12	CO-LF	2,875,000	3,247,000
5	Vandevoorde and Vanhoucke (2006)	10	9	CO-EF	906,000	952,000
6	Valle and Soares (2006)	10	10	OB-OS	12,563,452	12,563,452
7	Singletary (2006)	13	14	CU-LF	12,592,048	12,585,123
8	Author et al. (2009)	20	27	CO-LF	17,691,282	20,238,868

TABLE 1. *Case projects*

overruns cost but finishes earlier than expected *(CO-EF)*, and only one is completed on budget and on schedule *(OB-OS)*.

Early *(10-25%)*, middle *(45-65%)* and late stage *(70-95%)* cost estimates are calculated with the proposed risk-adjusted model for each project according to the following procedure. First, the GGM's α, β and γ parameters are obtained by non-linear regression. For this, x time data normalized with respect to PD are used as the predictor for the GGM model. Corresponding AV and PV cost data y *(AV data normalized from time zero to AT and PV data normalized from AT onto project completion with respect to BAC)* are used as the response variable *(Authors, 2014)*. The complete procedure for obtaining the values for the three above parameters are given in Authors *(2014)*. Second, Equation 5 is applied to produce the estimates.

Then, to test accuracy and stability of the estimates at the various stages of project development, the percentage error *(PE%)* is calculated with Equation 6 as the relative deviation of the CEAC from actual CAC.

$$PE\% = \frac{CEAC - CAC}{CAC} * 100\%$$

EQUATION 6

PE% results are compared to the estimate accuracy obtained with the base model to verify whether improvements are obtained with the new proposed model.

Finally, a sensitivity analysis of the percentage portion of BAC k within a range defined in literature *(Smith et al., 1999)* is carried out to confirm the validity of the model regardless of the value of the predetermined risk contingency budget. The analysis is complemented by a study on accuracy of the average and variance distribution for both the single project and for the set of projects.

5. Case Project Application

Here we present a complete application of the proposed procedure for the early cost estimate of Project #8, which input data are given in **Table 2**. The results for the other seven projects are summarized in the next section.

When the project is four time steps into its early execution, the ES*(4)* equals 3.32 with its associated SPI*(t)* of 0.83 and CF*(4)* of 1.20 that indicates a schedule delay.

To apply nonlinear regression with the GGM equation *(Equation 1)*, we utilize the Minitab® software tool. The following settings are entered: a Gauss-Newton algorithm, 200 maximum iterations, 1.0E-5 tolerance unit initial values for the regression parameters, 95% confidence level and convergence with minimum SSE. The values for the three regression parameters of the model are presented in **Table 3**.

Figure 2 shows the GGM's curve line that fits the project data with its associated Equation 7.

$$\text{Response} = 1.001198\ e^{[-e\ (2.616158 - 9.641258\ *\ \text{Predictor})]}$$

EQUATION 7

According to Equation 7, the values of the GGM*(x)* at points 1.00, *x* and CF*(x)* are as follows:

Replacement of these values into the base model allows to obtain:

GGM(1.00)	Response = 1.001198 $e^{[-e\ (2.616158 - 9.641258\ *\ 1.00)]}$ = 1.00
GGM(x) with x = 0.200	Response = 1.001198 $e^{[-e\ (2.616158 - 9.641258\ *\ 0.200)]}$ = 0.13
GGM[CF(x)] with CF(x) = 1.20	Response = 1.001198 $e^{[-e\ (2.616158 - 9.641258\ *\ 1.20)]}$ = 1.00

*CEAC(x) = AC(x) + {GGM[CF(x)] – GGM(x)} * BAC = 2.005.358+(1.001–0.137)*17,691,280 = 17,293,327*

While replacing the same values into the risk-adjusted model gives:

CEAC(x) = AC(x) + {GGM[CF(x)] – GGM(x)}BAC{1+k[α – GGM[CF(x)]]} =
2,005,358 + (1.001 – 0.137)*17,691,283 *[1 + 0.10*(1.0012- 1.001)] = 17,293,517

Period	PV	EV	AV	Predictor	Response
0	-	-	-	0.000	0.000
1	16,906	1,029	1,178	0.050	0.000
2	334,535	65,912	75,404	0.100	0.004
3	1,084,822	893,290	1,021,926	0.150	0.058
4	3,163,025	1,752,932	2,005,358	0.200	0.113
5	5,548,515	3,961,765	4,532,268	0.250	0.314
6	8,175,995	5,800,125	6,635,356	0.300	0.462
7	10,843,439	7,764,435	8,882,532	0.350	0.613
8	13,581,274	9,308,912	10,649,417	0.400	0.768
9	14,810,970	10,930,979	12,505,065	0.450	0.837
10	15,745,108	11,955,718	13,677,369	0.500	0.890
11	16,437,256	12,925,562	14,786,873	0.550	0.929
12	17,129,403	14,008,846	16,026,152	0.600	0.968
13	17,278,539	15,110,508	17,286,455	0.650	0.977
14	17,427,674	15,637,940	17,889,839	0.700	0.985
15	17,576,809	16,012,731	18,318,601	0.750	0.994
16	17,599,703	16,373,281	18,731,071	0.800	0.995
17	17,622,598	16,513,502	18,891,484	0.850	0.996
18	17,645,493	16,684,728	19,087,367	0.900	0.997
19	17,668,388	16,934,344	19,372,928	0.950	0.999
20	17,691,282	17,101,667	19,564,347	1.000	1.000
21		17,176,507	19,649,963		
22		17,245,028	19,728,352		
23		17,367,815	19,868,820		
24		17,498,535	20,018,364		
25		17,533,967	20,058,898		
26		17,639,525	20,179,657		
27		17,691,282	20,238,868		

TABLE 2. *Case project dataset*

Parameter	Parameters initial values	Parameters estimated values	Estimate SE	Summary Information
Theta1 ()	1.0	1.001198	0.003939	Iterations: 15 Final SSE: 0.0020183
Theta2 ()	1.0	2.616158	0.061074	DFE: 18 MSE: 0.0001121
Theta3 ()	1.0	9.641258	0.211247	S: 0.0105891

TABLE 3. *Regression parameters*

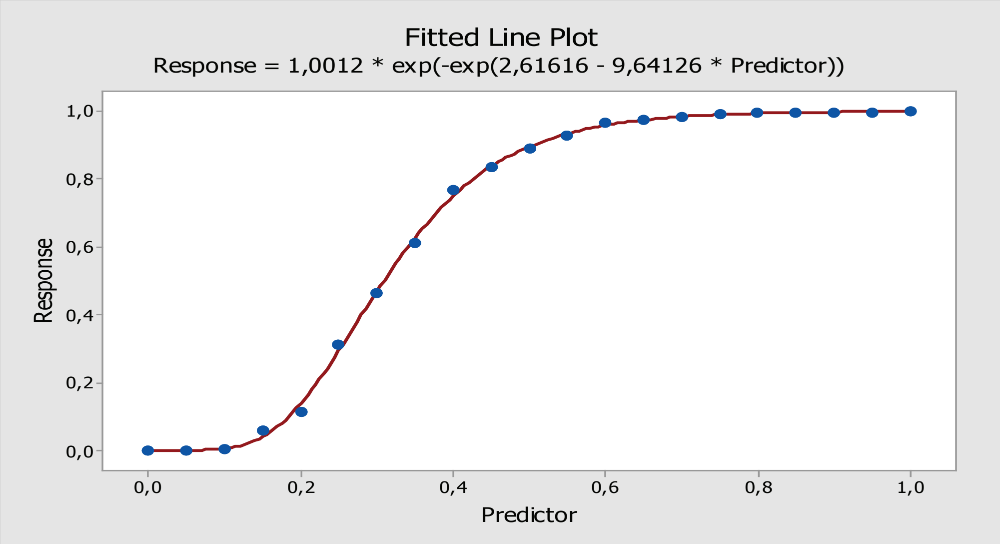

FIGURE 2. *Curve fitting for the case project*

Time	Algorithm		Prj1	Prj2	Prj3	Prj4	Prj5	Prj6	Prj7	Prj8
		CAC	61,564,285,700	59,183,600	349,379	3,247,000	952,000	12,563,452	12,585,123	20,238,868
EARLY	BASE	CEAC	59,935,481,304	56,611,850	367,692	2,930,518	919,825	12,505,219	12,656,114	17,293,327
EARLY	BASE	PE **[%]**	-2.65	-4.35	5.24	-9.75	-3.38	-0.46	0.56	-14.55
EARLY	RISK	CEAC	60,880,665,104	57,724,723	370,210	2,953,281	920,142	12,532,946	12,657,720	17,293,517
EARLY	RISK	PE **[%]**	-1.11	-2.47	5.96	-9.05	-3.35	-0.24	0.58	-14.55
MID	BASE	CEAC	55,125,141,023	57,192,070	397,170	3,214,922	905,070	12,756,901	12,947,137	18,822,201
MID	BASE	PE **[%]**	-10.46	-3.37	13.68	-0.99	-4.93	1.54	2.88	-7.00
MID	RISK	CEAC	55,360,343,159	57,780,738	400,092	3,246,842	905,468	12,794,322	12,975,358	18,822,278
MID	RISK	PE **[%]**	-10.08	-2.37	14.52	0.00	-4.89	1.84	3.10	-6.99
LATE	BASE	CEAC	59,102,851,961	59,832,837	356,568	3,216,207	935,688	12,955,972	13,411,878	19,480,383
LATE	BASE	PE **[%]**	-4.00	1.10	2.06	-0.95	-1.71	3.12	6.57	-3.75
LATE	RISK	CEAC	59,168,221,162	60,068,115	357,632	3,231,544	935,869	13,059,120	13,462,704	19,480,393
LATE	RISK	PE **[%]**	-3.89	1.49	2.36	-0.48	-1.69	3.95	6.97	-3.75

TABLE 4. *CEACs and PE with both models at various stages of project completion*

	EARLY STAGE					MIDDLE STAGE					LATE STAGE				
k, %	2.5	5.0	7.5	10.0	12.5	2.5	5.0	7.5	10.0	12.5	2.5	5.0	7.5	10.0	12.5
Prj 1	x	x	x	x	x	x	x	x	x	x	x	x	x		x
Prj 2	x	x	x	x	x		x	x	x	x					
Prj 3															
Prj 4	x	x	x	x	x		x	x	x	x	x	x	x	x	x
Prj 5	x	x	x	x	x		x	x	x	x	x	x	x	x	x
Prj 6	x	x	x	x	x										
Prj 7															
Prj 8	x	x	x	x	x		x	x	x	x	x	x	x	x	x
TOTAL	6	6	6	6	6	5	5	5	5	5	4	4	4	4	4

TABLE 5. *Algorithm stability to k% values*

Prj #	PE	k=2.5	k=5.0	k=7.5	k=10.0	k=12.5
1	Average	-5.53	-5.36	-5.20	-5.03	-4.86
	SD	4.27	4.37	4.48	4.59	4.71
2	Average	-1.93	-1.66	-1.39	-1.11	-0.84
	SD	2.74	2.57	2.41	2.26	2.11
3	Average	7.15	7.30	7.46	7.61	7.77
	SD	6.06	6.12	6.18	6.24	6.30
4	Average	-3.71	-3.53	-3.36	-3.18	-3.00
	SD	5.07	5.08	5.08	5.09	5.10
5	Average	-3.33	-3.33	-3.32	-3.31	-3.30
	SD	1.61	1.60	1.60	1.60	1.59
6	Average	1.51	1.62	1.74	1.85	1.96
	SD	1.87	1.94	2.02	2.09	2.17
7	Average	3.39	3.44	3.50	3.55	3.60
	SD	3.08	3.13	3.17	3.22	3.27
8	Average	-8.43	-8.43	-8.43	-8.43	-8.43
	SD	5.54	5.54	5.54	5.54	5.54

TABLE 6. *Variability of PE of each project to the k parameter (in %)*

6. Analysis of Results

From the analysis of results reported in **Table 4**, it can be observed that for six out of eight early estimates the risk-adjusted model generates better estimates than the base model *(projects #1, 2, 4, 5, 6 and 8)*. For mid stage estimates, however, only five projects out of eight *(projects #1, 2, 4, 5 and 8)* have more accurate estimates when using the risk-adjusted model and, in late stages, this count goes down to four projects *(#1, 4, 5, and 8)*.

The estimation method proposed in this paper proves to generate more accurate cost forecasts, especially in the early stages of a project, while the accuracy decreases gradually as far as the project progresses. In fact, when the progress is around 20%, as much as 75% of the project estimates get closer to the actual CAC.

This is an interesting result because it is during the early stage of a project that reliable estimates are needed for project managers to take timely and effective corrective actions. At this state just a few EVM data are available and this usually generates difficulties in obtaining accurate and reliable CEACs; the initial stage is one that has potential to influence the final project results by applying inexpensive performance corrections and adjustments.

Despite results presented thus far are encouraging, it is necessary to understand if the *k* parameter affects the validity of the proposed model. In fact, the size of the contingency budget, expressed as a function of the BAC, could influence the result of the CEAC. To this end, a sensitivity analysis is conducted in all early, middle, and late stages by varying *k* from 2.5 to 12.5%, which is reported by the literature to be a range of the risk contingency in relation to BAC *(Smith et al., 1999; Yeo, 1990; Mak et al., 2000)*. The results show that there is a substantial stability of the algorithm to *k*% values (**Table 5**), and this is definitely a positive point for the method that would ensure to be able to be applied regardless of the contingency value.

Finally, assuming the normality of input data, which is guaranteed by the hypothesis of the

Gaussian distribution, we assess the accuracy of the distribution of the estimates. By looking at single projects, average values and standard deviations *(SD)* of the PE stabilize at approximately same values, thus indicating a low sensitivity to the fluctuations of the *k* parameter (**Table 6**). This is a positive result as it guarantees the applicability of the model, whatever the size of the risk contingency budget.

Moreover, **Table 7** shows how the average forecast obtained with the proposed methodology slightly underestimate the final cost *(CAC)*. However, the CEAC becomes more accurate as *k* increases. This can be interpreted as a further justification and viability of the proposed risk-adjusted model that proves more accurate when a larger risk contingency budget is estimated on top of baseline cost and when risk plays an impacting role on the future behavior of project performance.

PE	k=2.5	k=5.0	k=7.5	k=10.0	k=12.5
Average	-1.36	-1.24	-1.12	-1.01	-0.89
SD	5.94	5.96	5.99	6.01	6.04

TABLE 7. *Variability of PE for the set of projects (in %)*

7. Conclusion

In an attempt to improve the methodologies to forecast the final cost of ongoing projects, this paper illustrates and tests on a sample of construction projects a combined index-regression based model. This model integrates into a comprehensive forecasting formula the impact of both integrated cost-schedule performance and S-shaped consumption of the risk contingency budget throughout the project execution. The method proves validity and applicability to a variety of project conditions and performance situations: it provides for accurate and stable CEACs during the various successive stages of project development and for different sizes of the originally estimated contingency budget.

The model has both theoretical and practical implications. The cost–schedule-risk relationship represented in the model equation is a contribution to creating a stronger connection between EVM and risk management research and to capturing the interconnected dynamics between the monitoring of cost baseline and contingency cost accounts in ongoing projects.

As a practical implication, the model is proposed in integration to ES-based nonlinear CEAC formulae as a contingency-adjusted mixed index-regression CEAC tool to be used especially during the early and mid periods of project monitoring. At these stages of project monitoring, great is the need for precise estimates with regard to expected future performance of complex projects, while maintaining computational simplicity.

Future research is directed towards replacing the assumption that contingency cost is consumed in line with the project's progress with more refined risk assessment and management methodologies that could better encapsulate the real expenditure of the contingency based on risk incurred along the project execution *(Xie et al., 2012)*. However, this further exploration would be needing to preserve the relatively simple formula and procedure to compute the CEAC. Also, since the method has been tested solely on construction projects, it is suggested for future application to a larger variety of projects at different progress stages and for diffusion in various industries.

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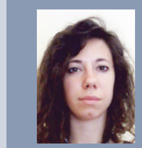

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